AGU ADVANCING EARTH AND SPACE SCIENCES

Geophysical Research Letters

RESEARCH LETTER
10.1029/2023GL105817

Key Points:

- A significant increasing trend in the frequency of compound dry and wet (CDW) extremes was observed across global rice croplands
- The risk of rice yield loss caused by CDW extremes can be twice as high as the risk from individual wet and dry extremes
- Global rice croplands face a 43% higher risk of rice yield loss caused by dry-to-wet extremes compared to wet-to-dry extremes

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. Wang,
shuo.s.wang@polyu.edu.hk

Citation:

Chen, H., & Wang, S. (2023). Compound dry and wet extremes lead to an increased risk of rice yield loss. *Geophysical Research Letters*, *50*, e2023GL105817. https://doi.org/10.1029/2023GL105817

Received 4 AUG 2023
Accepted 1 DEC 2023

Author Contributions:

Conceptualization: Shuo Wang
Data curation: Huijiao Chen
Formal analysis: Huijiao Chen, Shuo Wang
Funding acquisition: Shuo Wang
Investigation: Shuo Wang
Methodology: Huijiao Chen
Project Administration: Shuo Wang
Resources: Shuo Wang
Software: Huijiao Chen
Supervision: Shuo Wang
Validation: Huijiao Chen, Shuo Wang
Visualization: Huijiao Chen
Writing – original draft: Huijiao Chen
Writing – review & editing: Shuo Wang

Compound Dry and Wet Extremes Lead to an Increased Risk of Rice Yield Loss

Huijiao Chen[1] and Shuo Wang[1,2]

[1]Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong, China, [2]Research Institute for Land and Space, The Hong Kong Polytechnic University, Hong Kong, China

Abstract Extreme dry and wet events can result in significant crop yield losses. However, the impact of consecutive occurrence of dry and wet extremes on crop yield remains unclear. Here, we investigate the hotspots of compound dry and wet (CDW) extremes across global rice croplands and their impacts on rice yield. We identify a significant increasing trend in the frequency of CDW extremes during 1981–2016. The risk of yield loss caused by CDW extremes can be twice as high as the risk from individual wet and dry extremes. Furthermore, we find that global rice croplands face a 43% higher risk of rice yield loss due to dry-to-wet extremes compared to wet-to-dry extremes. Our findings provide new insights into the sustainability of global rice production and food security in the face of compound hydrological extremes.

Plain Language Summary It is widely recognized that compound events may exert larger impacts on crop production compared to individual extremes. Here, we investigate the consecutive occurrence of dry and wet (CDW) extremes during the rice-growing season and estimate their impacts on rice yield. We observe a significant increase in the frequency of CDW extremes across global rice croplands during the rice-growing season from 1981 to 2016. The CDW extremes exert a larger impact on rice yield loss compared to individual wet and dry extremes. The CDW extremes, characterized by longer durations of both dry and wet extremes and faster transitions between them, have an even more adverse influence on rice yield. The risk of yield loss caused by CDW extremes is 200% higher than the risk from individual wet and dry extremes. Furthermore, global rice croplands face a 43% higher risk of yield loss due to dry-to-wet extremes than wet-to-dry extremes.

1. Introduction

Rice is a food staple for more than 4 billion people around the world (CGIAR, 2022). The rice yield is highly sensitive to temperature and water stress throughout the growing season (Lesk et al., 2016). Rice yields have become less stable due to the increasing climate extremes (Alizadeh et al., 2020; Qing et al., 2022; Raymond et al., 2022), raising serious concerns associated with rice price volatility (Iizumi et al., 2013; Tigchelaar et al., 2018; B. Zhang et al., 2023) and food insecurity (Battisti & Naylor, 2009; Qi et al., 2022; Zscheischler & Fischer, 2020). Thus, recent studies investigated the impacts of climate extremes on crop yield reduction, such as heatwaves (Lobell et al., 2013; You et al., 2023; C. Zhao et al., 2017), droughts (Dietz et al., 2021; Hendrawan et al., 2022; Leng & Hall, 2019), and extreme rainfalls (Fu et al., 2023; Li et al., 2019).

Previous studies highlighted that compound events (two or more extreme events occur simultaneously or in succession) have even more destructive impacts on crop yields than individual extremes (H. Chen et al., 2023; Zscheischler et al., 2018, 2020), such as compound hot-dry extremes (Hamed et al., 2021; Lesk et al., 2021, 2022; Ribeiro et al., 2020; Zampieri et al., 2017) and compound hot-dry-wind extremes (H. Zhao et al., 2022). Particularly, the sequential occurrence of hydrological extremes (e.g., dry-to-wet extremes) could lead to more complex consequences (Qing et al., 2023). Such compound extremes have been observed to either enhance (Dodd et al., 2015; Linquist et al., 2015) or diminish crop yields (Xiong et al., 2018; R. Zhu et al., 2020). The sequence of dry/wet extreme occurrences trigger varying degrees of complex responses, defined by diverse and occasionally contradictory signaling pathways. Consequently, the ultimate yield impacts of climate extremes reflect intertwined physiological responses to multiple facets of the climate (Lesk et al., 2022).

For example, in 2017, Sri Lanka experienced the most severe drought in 40 years, which was then compounded by the worst torrential rains in 14 years. This sequence of events led to devastating floods and landslides, causing a 40% reduction in rice production and leaving approximately 900,000 people facing food insecurity (FAO, 2017). Similarly, a severe drought was followed by massive flooding in Pakistan's Singh province in 2022, resulting in a 31% decrease in the rice harvest (Kunbhar, 2022). These flooding incidents exemplify the extreme consequences of excessive wet conditions. These news emphasize the devastating consequences of dry-to-wet extremes. However, there has been limited effort to conduct an in-depth investigation of potential impacts of dry-to-wet extremes on crop yields at a global scale, especially within the context of climate change. Despite the expected increase in the occurrence of dry-to-wet extremes in a warming climate (H. Chen & Wang, 2022; H. Chen, Wang, & Wang, 2020; H. Chen, Wang, Zhu, & Zhang, 2020; Swain et al., 2018; Tan et al., 2023), the absence of clear evidence for the impact of dry-to-wet extremes on crop yields has rendered crop modelers to overlook their potential effects.

This study aims to provide a comprehensive assessment of regional hotspots and dynamic evolution of compound dry and wet (CDW) extremes during the rice-growing season, based on the ERA5 data set and the weekly Self-Calibrated Palmer drought severity index (scPDSI). We will quantify the risk of rice yield loss caused by CDW extremes by using a copula-based model, based on gridded yield observations. The copula-based models are powerful tools for assessing the probabilistic impacts of compound extremes on crop yields at a global scale (Feng et al., 2019). Our findings will provide significant implications for better understanding potential impacts of CDW extremes on rice yield, contributing to the advance in rice yield modeling and enhancing the resilience of rice production systems.

2. Data and Methods

2.1. Rice Yield Anomaly

The Crop Calendar Data set provides relatively accurate planting and harvesting dates for each rice cultivation globally, with a spatial resolution of 0.5° (Sacks et al., 2010). Here, the rice-growing season, defined as the number of weeks between the seeding (planting date, Figure S1a in Supporting Information S1) and maturity week (Figure S1d in Supporting Information S1), remains consistent within each growth cycle during 1981–2016 (Figure S1e in Supporting Information S1). CDW extremes occurring during the critical growth stages of rice can significantly influence rice yield (see a detailed description of how rice yield responds to extreme events in Text S1 in Supporting Information S1).

The crop calendar is also utilized in the development of the Global Data set of Historical Yield (GDHY) for major rice and secondary rice yields (Iizumi & Sakai, 2020), providing a global data set of gridded rice yields for the period of 1981–2016, with a spatial resolution of 0.5°. The GDHY data set comprises agricultural census statistics and satellite remote sensing, which has been widely used as a primary source in recent global crop-climate studies (Hamed et al., 2021; Hendrawan et al., 2022; Kim et al., 2021; P. Zhu et al., 2021).

The relative yield anomaly (y_t) is calculated for each grid cell, as shown in Equation 1. The anomaly represents the difference between the actual yield (Y_t) and the expected yield (U_t), divided by the expected yield (U_t).

$$y_t = \frac{Y_t - U_t}{U_t} \tag{1}$$

where Y_t is the rice yield value (tons per hectare, t/ha) and U_t is the expected yield value (t/ha) at year t. U_t is estimated based on a locally weighted scatterplot smoothing regression (LOESS). LOESS is one of well-known de-trending methods for studying crop yields (Jägermeyr et al., 2021; Troy et al., 2015), which allows us to filter out the overall yield increase resulting from technological advances, improvements in seeds, rising CO_2, and other environmental factors (Figure S3 in Supporting Information S1; Hendrawan et al., 2022; Ye et al., 2015; Lu et al., 2017). The yield loss is defined as relative yield anomalies below −10% of the expected yields ($y_t < -0.1$; Ben-Ari et al., 2018).

This study focuses on the top 20 rice-producing countries (Table S1 in Supporting Information S1), which play a crucial role in the global food market and security (Lobell et al., 2013; Matiu et al., 2017). These countries collectively account for 87% of total rice production globally during 1981–2016. Therefore, any rice yield loss in these countries could significantly affect global food trade and food security.

2.2. Identification of Compound Dry and Wet Extremes

Gridded daily precipitation and temperature were obtained from the ERA5 data set with a spatial resolution of 0.25° for the period of 1981–2016. We utilized the ERA5 data set for our primary analysis, and tested the sensitivity of our results (see a detailed description and evaluation of the three data sets in Text S2 in Supporting Information S1) using the Climate Prediction Center (CPC) Unified V1.0 (M. Chen et al., 2008) and Multi-Source Weighted-Ensemble Precipitation (MSWEP) V2.2 (Beck et al., 2019). Weekly averages of precipitation and

10.1029/2023GL105817

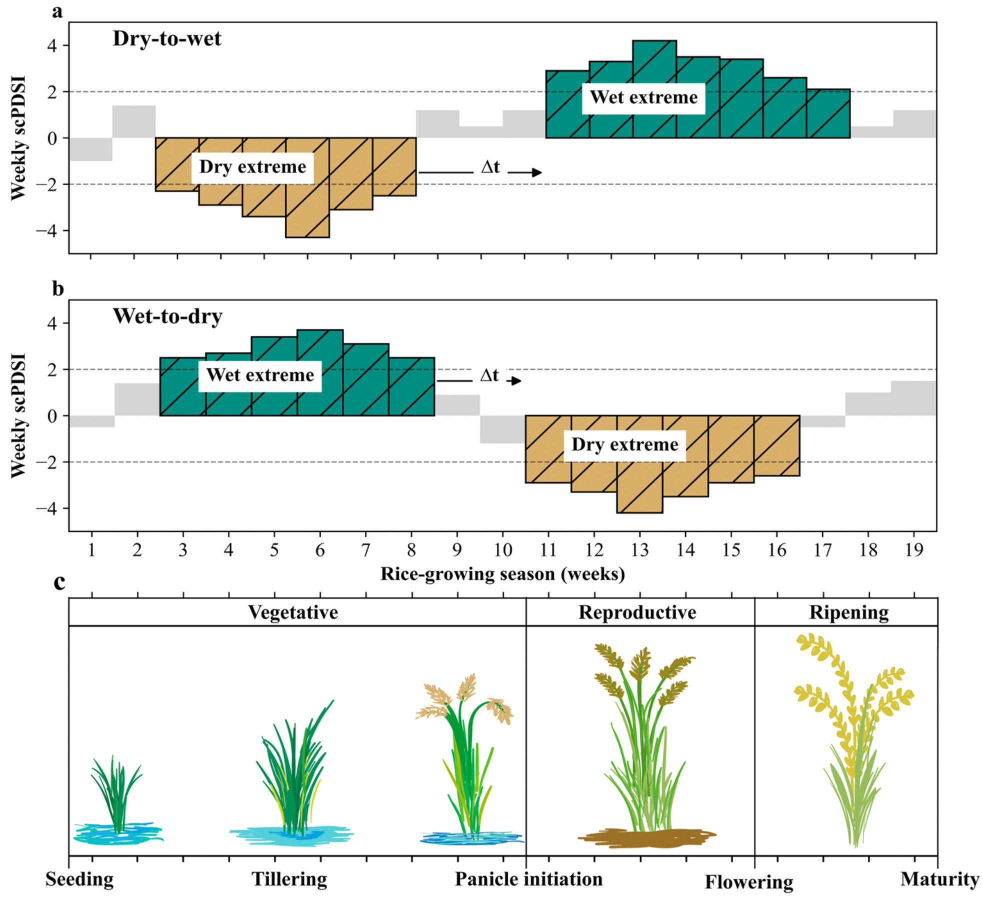

Figure 1. Schematic for the identification of compound dry and wet (CDW) extremes throughout the rice-growing season. The bar represents the weekly Self-Calibrated Palmer Drought Severity Index (scPDSI) value. Dry/wet events are detected when the weekly scPDSI exceeds/falls the predefined threshold. Dry (wet) extreme is defined as the dry (wet) event with the longest duration during a specific rice-growing season (Figure S3 in Supporting Information S1). Δt represents the weeks of transition between dry extreme and wet extreme during a specific rice-growing season. (a) Dry-to-wet extreme is defined when dry extreme occurs prior to wet extreme within the rice-growing season. (b) Wet-to-dry extreme is defined when wet extreme occurs prior to dry extreme. (c). Flowchart showing the key stages of rice growth throughout the growing season.

temperature were then calculated for the rice-growing season (Figure S1e in Supporting Information S1). These climate variables were interpolated to match the 0.5° resolution of the GDHY crop yield data set, so as to examine the relationship between climate variables and crop yields at a global scale.

The weekly Self-Calibrated Palmer drought severity index (scPDSI; Palmer, 1965; Wells et al., 2004) has been widely used to examine crop-climate interactions (Venkatappa et al., 2021; X. Zhu & Troy, 2018). A detailed calculation of scPDSI can be seen in Text S3 in Supporting Information S1. The scPDSI value of −2 was used as the threshold to identify dry weeks, while the scPDSI value of +2 was selected as the threshold to identify wet weeks (Venkatappa et al., 2021). Specifically, wet extreme was defined as the wet event with the longest duration, representing excessive moisture conditions for rice growth. Similarly, dry extreme was defined as the dry event with the longest duration, indicating the most severe water deficit condition for rice growth (see a detailed selection of wet and dry extremes in Text S4 and Figure S3 in Supporting Information S1).

For the occurrence of dry and wet extremes during the rice-growing season, the climate conditions can be classified into four categories: normal condition, individual dry extremes, individual wet extremes, and CDW extremes (including dry-to-wet extremes and wet-to-dry extremes). We defined three primary features of CDW extremes: transition rate, duration ratio, and frequency (Figure 1). Transition rate represents the ratio of weeks (Δt) between the termination of dry (or wet) extremes and the onset of wet (or dry) extremes to the total number of weeks throughout the rice-growing season. Duration ratio is the ratio of the number of weeks for CDW extreme duration to the total number of weeks throughout the rice-growing season, which combines the durations of dry and wet extremes. Frequency indicates the total number of years experiencing CDW extremes (dry-to-wet or wet-to-dry extremes) in each grid cell.

2.3. Definition of Yield Loss Risk

We used a copula-based model to estimate the potential impacts of dry or/and wet extremes on rice yields during the rice-growing season. Copulas are well suited for accurately capturing extreme events such as drought and floods since they can effectively treat the tails of the distribution (B. Zhang et al., 2022). Therefore, the probabilistic assessment of the impacts of climate extremes on rice yields can be conducted based on the conditional distribution of the severity of dry or wet extremes. Here, we considered five commonly used bivariate copula families (Table S2 in Supporting Information S1) to fit the joint probability distribution between the severity of dry extremes (d), the severity of wet extremes (w), and the relatively yield anomaly (y).

$$\rho_{dwy}(d,w,y) = \rho_d(d)\cdot\ \rho_w(w)\cdot\rho_y(y)\cdot C(d,w,\theta_{d,w})\cdot C(d,y,\theta_{d,y})\cdot C(h(w,d,\theta_{d,w}),h(y,d,\theta_{d,y}),\theta_{w,y|d}) \quad (2)$$

where $\rho_d(d)$, $\rho_w(w)$, and $\rho_y(y)$ are the marginal distributions of d, w, and y, respectively. C represents the copula density. $\theta_{d,w}$, $\theta_{d,y}$, and $\theta_{w,y|d}$ represent the parameters of bivariate copula; the h-function is the conditional probability distribution function.

The conditional cumulative probability $P(.|.)$ is determined using the canonical vine (C-vine) and the drawable vine (D-vine) structures (Alidoost et al., 2019; B. Zhang et al., 2022). Each bivariate copula in the vine structure has one parameter related to Kendall's t correlation between the severities of dry and wet extremes and the relative yield anomaly. We estimated the copula parameters using the maximum likelihood estimation method. An appropriate structure was then identified using the sequential maximal spanning tree algorithm (Dißmann et al., 2013) based on the Akaike's Information Criteria (Akaike, 1974). When the vine structure is determined, 2,000 simulations is generated based on the values extracted from the severity of dry extremes, the severity of wet extremes, and the relative yield anomaly. Thus, the conditional cumulative distribution function of yield loss ($y_t < -0.1$) under CDW extremes can be expressed as:

$$P\,(y|\,d,w) = \frac{\partial C_{y,w|d}\,(P\,(y|\,d),P\,(w|\,d))}{\partial P\,(w|\,d)} = h\big[h(y,d,\theta_{d,y}),h(w,d,\theta_{d,w}),\theta_{w,y|d}\big] \quad (3)$$

The inverse form of Equation 3 can be used to estimate the risk of yield loss caused by CDW extremes based on probabilistic model simulations:

$$\hat{y} = f(d,w,\tau) = P_y^{-1}\left\{h^{-1}\left(h^{-1}(\tau|h(P_w(w)|P_d(d),\theta_{d,w}),\theta_{w,y|d})|P_d(d),\theta_{d,y}\right)\right\},\tau\in(0,1) \quad (4)$$

where τ indicates random probability levels (e.g., $\tau = 0.01, 0.1, \ldots, 0.9$); P indicates cumulative marginal functions. To improve the reliability of model results, Markov Chain Monte Carlo simulations were used to generate multiple (e.g., 500) samples of τ from the uniform distribution $U(0,1)$.

3. Results

3.1. Hotspots and Trends of CDW Extremes

Figures S4 and S5 in Supporting Information S1 present the frequency of occurrence of CDW extremes based on weekly scPDSI during the rice-growing season from 1981 to 2016. A prominent spatial cluster with a higher frequency of CDW extremes in the top 10 rice-producing countries, including China, Brazil, Peru, Myanmar, India, Indonesia, Nigeria, Laos, Colombia, and Viet Nam. Wet extremes in Brazil and Nigeria exhibit a higher frequency than CDW extremes, while dry extremes are more frequent than CDW extremes in Nigeria, Myanmar, Laos, and Viet Nam. Specifically, CDW extremes can be further divided into dry-to-wet and wet-to-dry extremes. A higher frequency of occurrence of dry-to-wet extremes is found in North China and South Brazil (Figure S5 in Supporting Information S1). Meanwhile, more frequent wet-to-dry extremes are observed in South China and North Brazil (Figure S5 in Supporting Information S1). These findings provide insights into the hotspots of CDW extremes in the key rice-producing regions.

To assess of the temporal variation in the frequency of extreme events, we implemented a time series of moving windows approach (ranging from 13 to 23 years). The slope of the ordinary least square regression of these sensitivities against time was considered as the temporal trend in frequency. Across the period of 1981–2016 in global

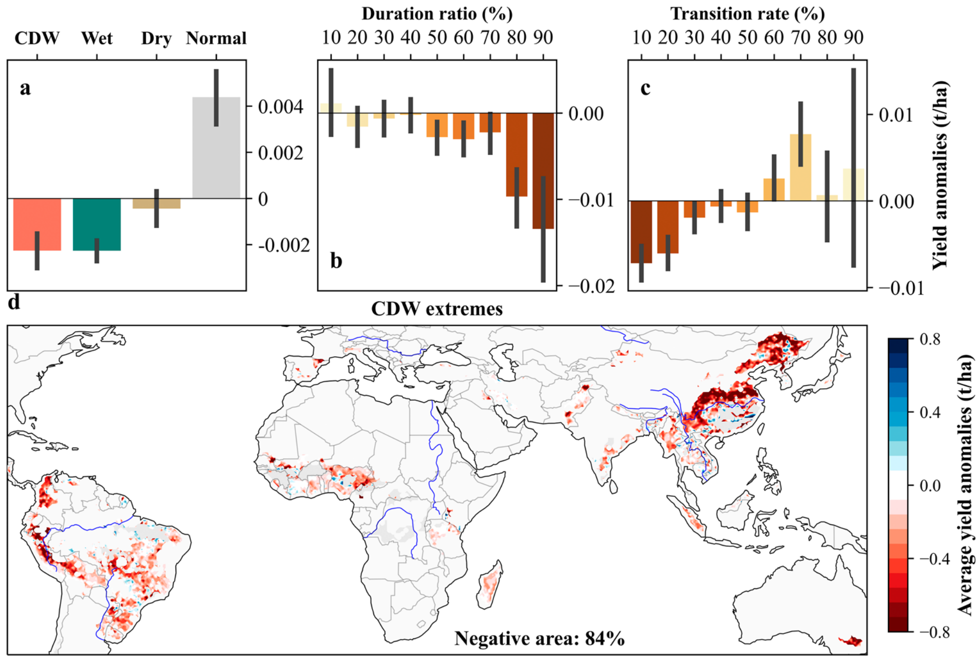

Figure 2. (a) Estimated effects of compound dry and wet (CDW) extremes, wet extremes, dry extremes, and normal conditions on relative rice yield anomalies (t/ha). (b) Estimated effects of CDW extremes with different duration ratios (i.e., the ratio of the number of weeks of CDW extreme duration to the total number of weeks in the rice-growing season) on rice yield. (c) Estimated effects of CDW extremes with different transition rates on rice yield. Black line represents the error bars from 5% to 95% confidence interval. (d) Spatial distributions of the average effects of CDW extremes on rice yield from 1981 to 2016. Gray color represents the spatial extent of rice croplands where CDW extremes are not observed.

rice croplands, Figure S6 in Supporting Information S1 shows a significant increasing trend in the frequency of dry-to-wet extremes ($R^2 = 0.92$, $p < 0.01$), wet-to-dry extremes ($R^2 = 0.81$, $p < 0.01$), and dry extremes ($R^2 = 0.92$, $p < 0.01$). Conversely, wet extremes ($R^2 = 0.92$, $p < 0.01$) show a significantly decreasing trend. These results align with the findings of Y. Zhang et al. (2023) and Tan et al. (2023), showing an upward trend in the consecutive occurrence of droughts and floods over China and global land area, respectively. It is thus crucial to investigate the impact of CDW extremes on rice yield since CDW extremes show an increased trend but there is currently a lack of adaptation and mitigation strategies to reduce the impact of CDW extremes on rice cultivation.

3.2. Impacts of CDW Extremes on Rice Yield

To evaluate the significant rice yield loss during CDW extremes occurrence, we utilized a Superposed Epoch Analysis (SEA; Text S5 in Supporting Information S1). SEA is used to investigate whether rice yield anomalies during CDW extremes significantly differ from random variability. The most prominent yield loss response, at −0.29 (t/ha) relative to the 5-year pre-event mean, occurs during CDW extremes (Figure S7 in Supporting Information S1). This indicates that the yield responses during CDW extremes are lower than what would be expected by random variability. In addition, since the relative yield anomalies under different dry and wet extremes exhibited non-normal distributions (Figure S8 in Supporting Information S1), we performed a non-parametric Kruskal-Wallis test (Kruskal & Wallis, 1952), as shown in Figure 2a. The Kruskal-Wallis test (Text S6 in Supporting Information S1) is used to determine if there are significant differences in the medians of relative yield anomalies under CDW extremes, wet extremes, and dry extremes. The median values of −2.27 (t/ha $\times 10^{-3}$), −2.25 (t/ha $\times 10^{-3}$), −0.438 (t/ha $\times 10^{-3}$), and 4.386 (t/ha $\times 10^{-3}$) were derived for relative yield anomalies under CDW extremes, wet extremes, dry extremes, and normal condition, respectively. The difference between these groups is statistically significant ($p < 0.001$). In comparison, the yield anomalies under CDW extremes are the largest, followed by wet extremes and dry extremes. This aligns with previous studies that have reported a greater sensitivity of rice yield to dry-wet transitions compared to consecutive dry or consecutive wet conditions (Gao et al., 2019; Huang et al., 2019; Xiong et al., 2018; R. Zhu et al., 2020).

10.1029/2023GL105817

Figure 2b shows the yield effects of CDW extremes with varying duration ratios (i.e., the ratio of the number of weeks for CDW extreme duration to the total number of weeks throughout the rice-growing season). Figure 2c presents the yield effects across different transition rates. The impact of CDW extremes characterized by higher transition rates on rice yield becomes more complex and significantly uncertain. Notably, CDW extremes, characterized by prolonged durations and more rapid transitions between two extremes, have a more pronounced adverse influence on rice yield. Similarly, the longer durations of wet and dry extremes could intensify the negative impact on rice yield (Figure S9 in Supporting Information S1).

Figure 2d shows the average yield anomalies under CDW extremes during the rice-growing season from 1981 to 2016. Generally, over 84% of global rice croplands experienced a negative impact from CDW extremes, primarily concentrated in the northern regions of China, Myanmar, Nigeria, Peru and Colombia. This pattern aligns well with the average yield anomalies under CDW extremes among the ERA5, MSWEP, and CPC precipitation data sets (Figure S10 in Supporting Information S1). The hotspot pattern, characterized by CDW extremes occurring more frequently, intensifies the negative impact on rice yield, resulting in yields lower than expected. In addition, about 90% of global rice croplands experienced a negative impact from wet extremes (Figure S11a in Supporting Information S1), which aligns with previous studies reporting that wet extremes can reduce rice yields (Fu et al., 2023; Jian et al., 2020; Li et al., 2019). However, about 74% of global rice croplands exposed to dry extremes experiences a smaller impact compared to areas affected by CDW extremes and wet extremes (Figure S11b in Supporting Information S1).

3.3. Risk of Yield Loss Under CDW Extremes

To further assess the response of rice yield loss to CDW extremes, the risk of rice yield loss ($y_t < -0.1$, relative yield anomalies below −10% of the expected yields) caused by CDW extremes is estimated using a copula-based model (Section 2.3). Figures 3a–3c show the spatial distributions of the risk of rice yield loss under CDW, wet, and dry extremes, respectively. CDW and dry extremes pose risk to more than 73% of global rice croplands, while wet extremes affect around 90% of global rice croplands. Specifically, a higher risk of yield loss under CDW extremes is found in the northern part of China, Bangladesh, and Pakistan, surpassing the risk caused by individual wet and dry extremes. The spatial patterns remain consistent even when risks are assessed using MSWEP and CPC data sets, with discrepancies observed particularly over the southern regions of China (Figure S12 in Supporting Information S1).

Figure 3d and Figure S13 in Supporting Information S1 show the area-weighted risk of yield loss under CDW, wet, and dry extremes across global and top 20 rice-producing countries. It reveals that nearly all these countries face double the risk of yield loss under CDW extremes compared to individual wet and dry extremes. Conversely, Spain and Mali exhibit the highest risk of yield loss under dry extremes (Figure S13 in Supporting Information S1). These results reveal the variations in yield loss risk under dry and wet extremes across different regions, highlighting the complexity of compound extremes and their diverse impacts on rice yield (Li et al., 2019). Overall, the risk of rice yield loss caused by CDW extremes is twice as high as the risk from individual wet (median 6.5%) and dry extremes (median 5.3%), with median values reaching as high as 12.8%.

Figure S14 in Supporting Information S1 displays the risk of yield loss caused by CDW extremes during shorter growing seasons (e.g., May-October in the northern part of China). CDW extremes affect approximately 41% of global rice croplands during the tillering-maturity growing season (Figure S14a in Supporting Information S1) and 14% during the panicle initiation-maturity growing season (Figure S14b in Supporting Information S1). Notably, the doubled risk of yield loss caused by CDW extremes, in comparison with individual wet and dry extremes, remains consistent regardless of the duration of rice-growing season (Figure S14c in Supporting Information S1). As these results are insensitive to the duration of rice-growing seasons, our study focuses on the seeding-maturity growing season.

Figure 4a displays the risk of rice yield loss caused by dry-to-wet extremes, revealing higher risks in the northern part of China, southern part of Brazil, and Nigeria. By contrast, Figure 4b illustrates the risk of rice yield loss caused by wet-to-dry extremes, showing higher risks in the southern part of China and the northern part of Brazil. The strong spatial complementarity might be attributed to the specific rice-growing seasons in these regions (Figure S1 in Supporting Information S1) and dry and wet extremes are controlled by the temporal variation in seasonal precipitation (Guo et al., 2020; Wang et al., 2008). Generally, dry-to-wet extremes pose

10.1029/2023GL105817

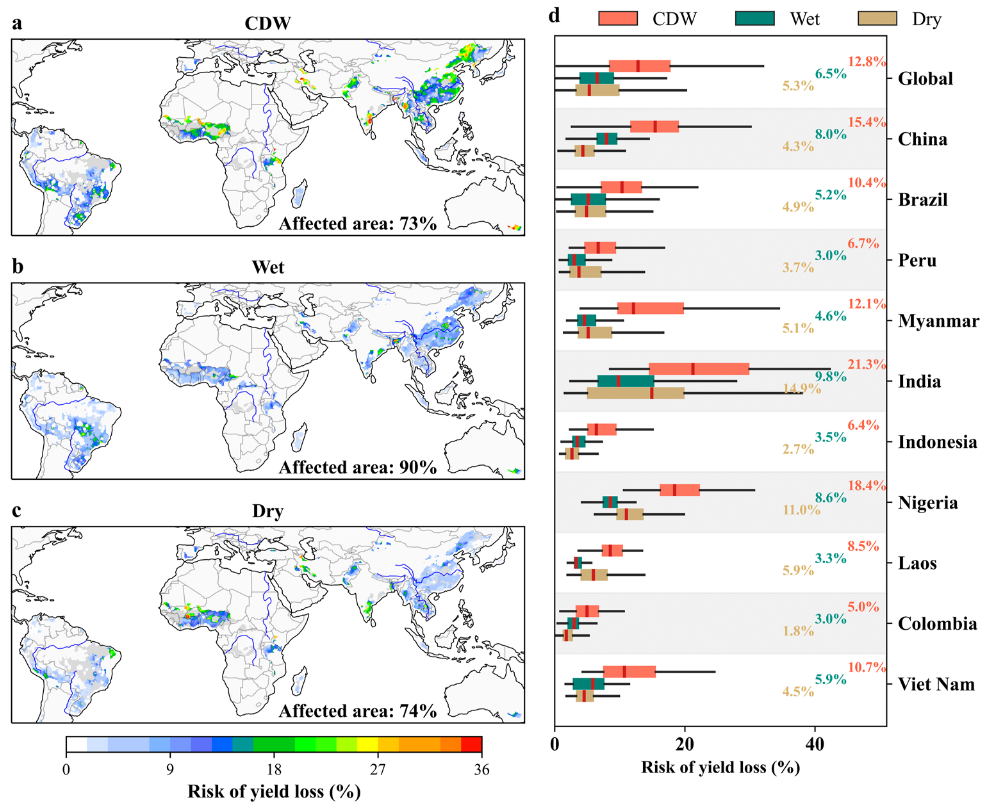

Figure 3. Spatial distributions of the risk of yield loss under (a) compound dry and wet (CDW) extremes, (b) wet extremes, and (c) dry extremes. Gray color represents the spatial extent of rice croplands where dry or wet extremes are not observed. (d) Area-weighted risk of yield loss across global and top 10 rice-producing countries. The percentages of red, green, and yellow represent the median values of risk of yield loss caused by CDW extremes, wet extremes, and dry extremes, respectively. The boxes represent the 25th and 75th percentiles. The whiskers represent 99% of the risk of yield loss.

risk to about 55% of global rice croplands, which is a larger proportion compared to the 37% of global rice croplands affected by wet-to-dry extremes. In addition, Figure 4c and Figure S15 in Supporting Information S1 present the area-weighted risk of yield loss caused by dry-to-wet extremes and wet-to-dry extremes across global and the top 20 rice-producing countries. Major rice-producing countries, including China, Brazil, India, Indonesia, Nigeria, Laos, Colombia, and Viet Nam, exhibit a higher risk of yield loss caused by dry-to-wet extremes compared to wet-to-dry extremes. Overall, the risk of yield loss caused by dry-to-wet extremes (median 14.5%) is 43% higher than the risk associated with wet-to-dry extremes (median 10.1%).

4. Discussion

Huang et al. (2019) demonstrated that the responses of root and yield related traits in rice to drought-flood abrupt alternation were not simply the additive effect of drought alone and flood alone; instead, there existed interactions (positive/negative compensation) between them. It is thus important to note that CDW extremes with shorter durations and slower transition rates (Figures 2b and 2c) can be considered as a practice similar to alternate wetting and drying (AWD) in rice cultivation. AWD involves intentionally allowing the soil to dry out periodically between irrigation events, resulting in mild wet-to-dry water fluctuations typically lasting from 1 to 10 days (R. Zhu et al., 2020). Previous studies have shown that AWD can positively impact rice growth and improve water management (Darzi-Naftchali et al., 2017; Dodd et al., 2015; Linquist et al., 2015; H. Zhang et al., 2009). Therefore, it is crucial to differentiate between the mild fluctuations in soil water conditions within a reasonable range (from 1 to 10 days), and more severe CDW extremes occur at a monthly scale (lasting for at least 30 days). This study highlights that, during the rice-growing season, more severe and prolonged CDW extremes can have detrimental effects on yield compared to mild fluctuations in soil water conditions (Figures 2b–2c). Moreover, AWD is a human-controlled irrigation practice that regulates the alternation between short wet and dry periods,

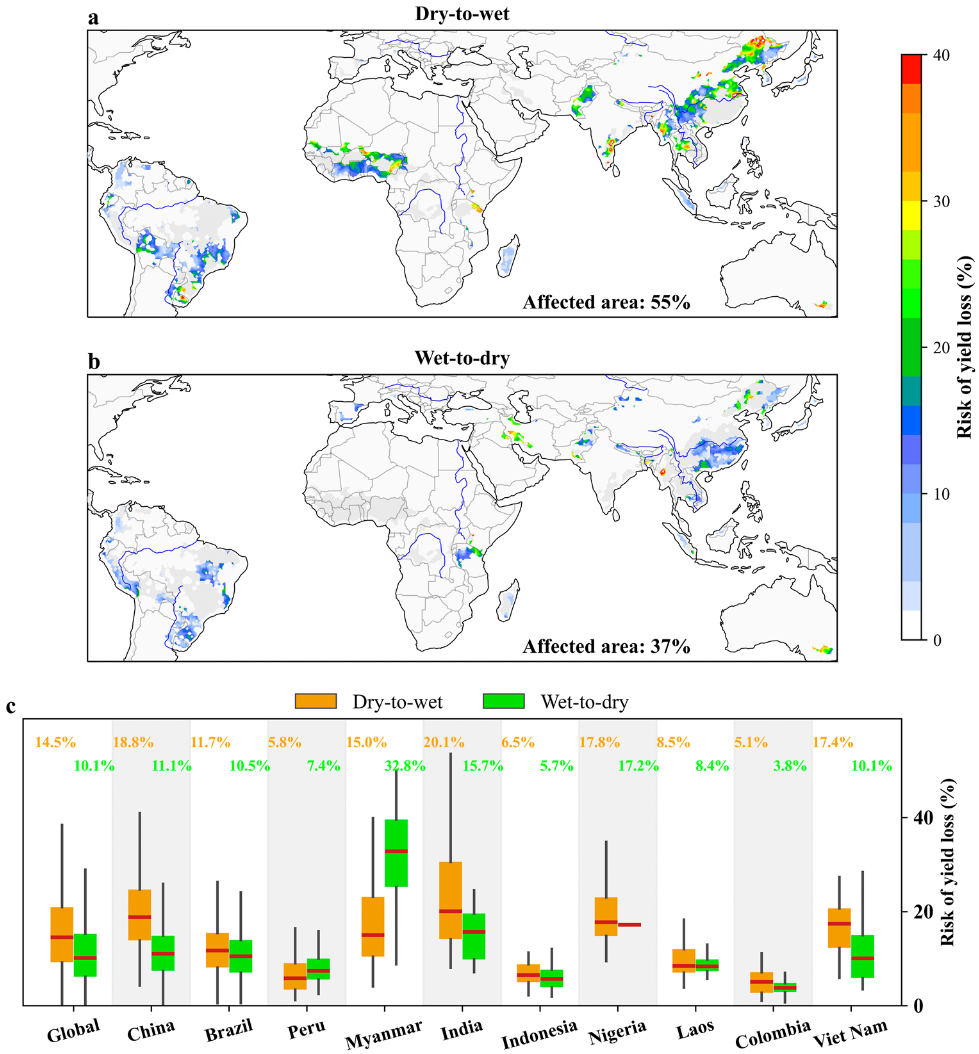

Figure 4. Spatial distributions of the risk of rice yield loss under (a) dry-to-wet extremes, and (b) wet-to-dry extremes. Gray color represents the spatial extent of rice croplands where compound dry and wet (CDW) extremes are not observed. (c) Area-weighted risk of yield loss across global and top 10 rice-producing countries. The percentages of orange and green represent the median values of risk of yield loss caused by dry-to-wet and wet-to-dry extremes, respectively. The boxes represent the 25th and 75th percentiles. The whiskers represent 99% of the risk of yield loss.

while CDW extremes are uncontrollable climate extremes, leading to more complex and unpredictable impacts on rice production.

To calculate yields constrained by water supply, we also assessed yield fluctuations under different irrigation patterns based on the MIRCA2000 (Portmann et al., 2010) and SPAM2010 (Yu et al., 2020) irrigated data sets (see Text S7 in Supporting Information S1). As anticipated, rice croplands with higher irrigated ratios exhibit minimal impacts of CDW extremes on relative yield changes (Figure S16 in Supporting Information S1), indicating a lower sensitivity to these extremes owing to the prevalence of irrigation. The results of dry extremes are similar to those of CDW extremes. Conversely, irrigation shows a minimal contribution to reducing yield loss caused by wet extremes. Moreover, the impact of irrigation on rice yield under CDW extremes varies significantly among the top 10 rice-growing countries (Figure S17 in Supporting Information S1). This highlights the complex influence of these extremes on rice production, despite the role of irrigation in mitigating the sensitivity of rice yield to water variability stress.

However, additional factors (e.g., hot and cold conditions) may be embedded within the worst-case scenarios. Hot and cold extremes are defined as the 95th and 5th of the weekly temperature during the rice-growing cycle in each grid. In comparison, the yield anomalies under CDW extremes coupled with back-to-back hot and cold extremes show the greatest losses, followed by CDW extremes coupled with cold extremes, CDW extremes coupled with hot extremes (Figure S18 in Supporting Information S1). Similarly, the yield anomalies under wet extremes coupled with back-to-back hot and cold extremes are most severe. Generally, CDW extremes combined with back-to-back hot and cold extremes create the worst-case scenario and result in the largest yield losses. Results for wet extremes and dry extremes align closely with those for CDW extremes.

Our study provides new insights into CDW extreme-induced mechanisms of rice yield losses at a global scale and thus acts as an essential complement to field experiments (Hoover et al., 2022; Xiong et al., 2018; R. Zhu et al., 2020). The latter allows for a direct control of water and heat variables but is necessarily restricted to a few locations and has until now only sparse coverage of rice croplands. Therefore, experimental bottom-up and top-down regression approaches are both necessary to elucidate crop response under climate change (Schauberger et al., 2017). The proposed copula-based model allows examining probable yield responses to dry and wet extremes across a wide spatial area. Our results show that the CDW extremes are an under-appreciated risk to rice production in the world's rice production areas, and such risk should be further investigated using the process-based crop models.

Our study has certain limitations. First, accurately quantifying farmer adaptation strategies in response to dry and wet extremes remains challenging. Future research could explore this by conducting surveys or utilizing social-economic data to gain insights into the adaptive measures employed by farmers. In addition, dry and wet extremes adversely affect various physiological functions of rice, prompting the plant to acclimate to these unfavorable conditions (Bhandari et al., 2023). Physiological traits in rice (e.g., stomatal conductance, leaf water content, and photosynthetic rate) can exhibit variations in response to these extremes, depending on rice type, growth stage, and regions (Lesk et al., 2022). Genetic breeding of crops implies that specific crops may develop different tolerance levels (Bin Rahman & Zhang, 2022). Different croplands may cultivate various varietals of the same crop with varying abilities to withstand these extremes.

5. Conclusions

This study investigates the hotspots of CDW extremes over global rice croplands and their impacts on rice yield from 1981 to 2016. Specifically, we examine the impacts of CDW, wet, and dry extremes on rice yield, which play a crucial role in advancing our understanding of back-to-back dry and wet extremes and in developing risk mitigation strategies.

Our findings reveal that CDW extremes exert the most significant influence on yield anomalies compared to individual wet and dry extremes. The CDW extremes, characterized by the prolonged duration and rapid shift between dry and wet extremes, exhibit a notable adverse impact on rice yield. The risk of rice yield loss caused by CDW extremes is twice as high as the risk from individual wet and dry extremes. The nearly double risks posed by CDW extremes in comparison to individual dry or wet extremes underscore the importance of assessing the impact of these compound extremes.

Globally, there is a relatively high frequency of CDW extremes in key rice-producing regions for the period of 1981–2016, encompassing countries such as China, Brazil, Peru, Myanmar, India, Indonesia, Nigeria, Laos, Colombia, and Viet Nam. This trend indicates an increased frequency of CDW extremes across global rice croplands. Various types of CDW extremes affecting rice yield differ across regions. Dry-to-wet extremes predominantly affect North China and South Brazil, while wet-to-dry extremes affect South China and North Brazil. The observed spatial differences may be attributed to specific rice-growing seasons in these regions and the temporal variation of seasonal precipitation (Guo et al., 2020). Global rice croplands face a 43% higher risk of yield loss due to dry-to-wet extremes compared to wet-to-dry extremes. These findings should draw the attention of relevant professionals, urging them to implement adaptive strategies in response to these compound extremes in a warming climate.

Data Availability Statement

All datasets used in this study are publicly available. The crop calendar dataset is available at Sacks et al. (2010). The Global Dataset of Historical Yield (GDHY) for major rice and secondary rice yields is available at Iizumi & Sakai. (2020). The ERA5 dataset is available at Hersbach et al. (2020). The Climate Prediction Center (CPC)

Unified V1.0 is available at M. Chen et al. (2008) and Multi-Source Weighted-Ensemble Precipitation (MSWEP) V2.2 is available at Beck et al. (2019). Relevant processed data is stored at H. Chen (2023).

Acknowledgments

This research was supported by the Hong Kong Polytechnic University (Project No. P0045957, P0043040).

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Alidoost, F., Su, Z., & Stein, A. (2019). Evaluating the effects of climate extremes on crop yield, production and price using multivariate distributions: A new copula application. *Weather and Climate Extremes*, *26*(July), 100227. https://doi.org/10.1016/j.wace.2019.100227

Alizadeh, M., Adamowski, J., Nikoo, M., AghaKouchak, A., Dennison, P., & Sadegh, M. (2020). A century of observations reveals increasing likelihood of continental-scale compound dry-hot extremes. *Science Advances*, *6*(39), 4571–4594. https://doi.org/10.1126/sciadv.aaz4571

Battisti, D., & Naylor, R. (2009). Historical warnings of future food insecurity with unprecedented seasonal heat. *Science*, *323*(5911), 240–244. https://doi.org/10.1126/science.1164363

Beck, H., Pan, M., Roy, T., Weedon, G., Pappenberger, F., Van Dijk, A., et al. (2019). Daily evaluation of 26 precipitation datasets using Stage-IV gauge-radar data for the CONUS. *Hydrology and Earth System Sciences*, *23*(1), 207–224. https://doi.org/10.5194/hess-23-207-2019

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., Van Der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. *Nature Communications*, *9*(1), 1627. https://doi.org/10.1038/s41467-018-04087-x

Bhandari, U., Gajurel, A., Khadka, B., Thapa, I., Chand, I., Bhatta, D., et al. (2023). Morpho-physiological and biochemical response of rice (*Oryza sativa L.*) to drought stress: A review. *Heliyon*, *9*(3), e13744. https://doi.org/10.1016/j.heliyon.2023.e13744

Bin Rahman, A., & Zhang, J. (2022). The coexistence of flood and drought tolerance: An opinion on the development of climate-smart rice. *Frontiers in Plant Science*, *13*, 860802. https://doi.org/10.3389/FPLS.2022.860802

CGIAR. (2022). *Consultive group on international agriculture*. RICE. Retrieved from https://ricecrp.org/importance-of-rice/

Chen, H. (2023). Compound dry and wet extremes lead to an increased risk of rice yield loss [Dataset]. Zenodo. https://doi.org/10.5281/zenodo.10071590

Chen, H., & Wang, S. (2022). Accelerated transition between dry and wet periods in a warming climate. *Geophysical Research Letters*, *49*(19), e2022GL099766. https://doi.org/10.1029/2022GL099766

Chen, H., Wang, S., & Wang, Y. (2020). Exploring abrupt alternations between wet and dry conditions on the basis of historical observations and convection-permitting climate model simulations. *Journal of Geophysical Research: Atmospheres*, *125*(9), e2019JD031982. https://doi.org/10.1029/2019JD031982

Chen, H., Wang, S., Zhu, J., & Wang, D. (2023). Projected changes in the pattern of spatially compounding drought and pluvial events over eastern China under a warming climate. *Earth's Future*, *11*(5), e2022EF003397. https://doi.org/10.1029/2022EF003397

Chen, H., Wang, S., Zhu, J., & Zhang, B. (2020). Projected changes in abrupt shifts between dry and wet extremes over China through an ensemble of regional climate model simulations. *Journal of Geophysical Research: Atmospheres*, *125*(23), e2020JD033894. https://doi.org/10.1029/2020JD033894

Chen, M., Shi, W., Xie, P., Silva, V. B., Kousky, V., Higgins, W., & Janowiak, J. (2008). Assessing objective techniques for gauge-based analyses of global daily precipitation. *Journal of Geophysical Research*, *113*(D4), 1049. https://doi.org/10.1029/2007JD009132

Darzi-Naftchali, A., Ritzema, H., Karandish, F., Mokhtassi-Bidgoli, A., & Ghasemi-Nasr, M. (2017). Alternate wetting and drying for different subsurface drainage systems to improve paddy yield and water productivity in Iran. *Agricultural Water Management*, *193*, 221–231. https://doi.org/10.1016/j.agwat.2017.08.018

Dietz, K. J., Zörb, C., & Geilfus, C. M. (2021). Drought and crop yield. *Plant Biology*, *23*(6), 881–893. https://doi.org/10.1111/plb.13304

Dißmann, J., Brechmann, E., Czado, C., & Kurowicka, D. (2013). Selecting and estimating regular vine copulae and application to financial returns. *Computational Statistics & Data Analysis*, *59*(1), 52–69. https://doi.org/10.1016/J.CSDA.2012.08.010

Dodd, I., Puértolas, J., Huber, K., Pérez-Pérez, J., Wright, H., & Blackwell, M. (2015). The importance of soil drying and re-wetting in crop phytohormonal and nutritional responses to deficit irrigation. *Journal of Experimental Botany*, *66*(8), 2239–2252. https://doi.org/10.1093/jxb/eru532

FAO. (2017). Special report: FAO/WFP crop and food security assessment mission to Sri Lanka. Retrieved from https://www.fao.org/3/i7450e/i7450e.pdf

Feng, S., Hao, Z., Zhang, X., & Hao, F. (2019). Probabilistic evaluation of the impact of compound dry-hot events on global maize yields. *Science of the Total Environment*, *689*, 1228–1234. https://doi.org/10.1016/j.scitotenv.2019.06.373

Fu, J., Jian, Y., Wang, X., Li, L., Ciais, P., Zscheischler, J., et al. (2023). Extreme rainfall reduces one-twelfth of China's rice yield over the last two decades. *Nature Food*, *4*(May), 416–426. https://doi.org/10.1038/s43016-023-00753-6

Gao, Y., Hu, T., Wang, Q., Yuan, H., & Yang, J. (2019). Effect of drought–flood abrupt alternation on rice yield and yield components. *Crop Science*, *59*(1), 280–292. https://doi.org/10.2135/cropsci2018.05.0319

Guo, B., Zhang, J., Meng, X., Xu, T., & Song, Y. (2020). Long-term spatio-temporal precipitation variations in China with precipitation surface interpolated by ANUSPLIN. *Scientific Reports*, *10*(1), 81. https://doi.org/10.1038/s41598-019-57078-3

Hamed, R., Van Loon, A., Aerts, J., & Coumou, D. (2021). Impacts of compound hot-dry extremes on US soybean yields. *Earth System Dynamics*, *12*(4), 1371–1391. https://doi.org/10.5194/ESD-12-1371-2021

Hendrawan, V., Kim, W., Touge, Y., Ke, S., & Komori, D. (2022). A global-scale relationship between crop yield anomaly and multiscalar drought index based on multiple precipitation data. *Environmental Research Letters*, *17*(1), 014037. https://doi.org/10.1088/1748-9326/AC45B4

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/qj.3803

Hoover, D., Hajek, O., Smith, M., Wilkins, K., Slette, I., & Knapp, A. (2022). Compound hydroclimatic extremes in a semi-arid grassland: Drought, deluge, and the carbon cycle. *Global Change Biology*, *28*(8), 2611–2621. https://doi.org/10.1111/GCB.16081

Huang, J., Hu, T., Yasir, M., Gao, Y., Chen, C., Zhu, R., et al. (2019). Root growth dynamics and yield responses of rice (*Oryza sativa L.*) under drought—Flood abrupt alternating conditions. *Environmental and Experimental Botany*, *157*(May 2018), 11–25. https://doi.org/10.1016/j.envexpbot.2018.09.018

Iizumi, T., & Sakai, T. (2020). The global dataset of historical yields for major crops 1981–2016. *Scientific Data*, *7*(1), 1–7. https://doi.org/10.1038/s41597-020-0433-7

Iizumi, T., Sakuma, H., Yokozawa, M., Luo, J., Challinor, A., Brown, M., et al. (2013). Prediction of seasonal climate-induced variations in global food production. *Nature Climate Change*, *3*(10), 904–908. https://doi.org/10.1038/nclimate1945

Jägermeyr, J., Müller, C., Ruane, A., Elliott, J., Balkovic, J., Castillo, O., et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nature Food*, *2*(11), 873–885. https://doi.org/10.1038/s43016-021-00400-y

Jian, Y., Fu, J., Li, B., & Zhou, F. (2020). Increased extreme hourly precipitation over China's rice paddies from 1961 to 2012. *Scientific Reports*, *10*(1), 1–12. https://doi.org/10.1038/s41598-020-67429-0

Kim, K., Doi, Y., Ramankutty, N., & Iizumi, T. (2021). A review of global gridded cropping system data products. *Environmental Research Letters*, *16*(9), 093005. https://doi.org/10.1088/1748-9326/ac20f4

Kruskal, W., & Wallis, W. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, *47*(260), 583–621. https://doi.org/10.1080/01621459.1952.10483441

Kunbhar, Z. (2022). *Floods after drought devastate Sindh's agriculture*. The Third Pole. Retrieved from https://www.thethirdpole.net/en/food/floods-after-drought-devastate-sindh-agriculture/

Leng, G., & Hall, J. (2019). Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Science of the Total Environment*, *654*, 811–821. https://doi.org/10.1016/J.SCITOTENV.2018.10.434

Lesk, C., Anderson, W., Rigden, A., Coast, O., Jägermeyr, J., McDermid, S., et al. (2022). Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment*, *3*(12), 872–889. https://doi.org/10.1038/s43017-022-00368-8

Lesk, C., Coffel, E., Winter, J., Ray, D., Zscheischler, J., Seneviratne, S., & Horton, R. (2021). Stronger temperature-moisture couplings exacerbate the impact of climate warming on global crop yields. *Nature Food*, *2*(9), 683–691. https://doi.org/10.1038/s43016-021-00341-6

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. https://doi.org/10.1038/nature16467

Li, Y., Guan, K., Schnitkey, G., DeLucia, E., & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, *25*(7), 2325–2337. https://doi.org/10.1111/gcb.14628

Linquist, B., Anders, M., Adviento-Borbe, M., Chaney, R., Nalley, L., Da Rosa, E., & Van Kessel, C. (2015). Reducing greenhouse gas emissions, water use, and grain arsenic levels in rice systems. *Global Change Biology*, *21*(1), 407–417. https://doi.org/10.1111/gcb.12701

Lobell, D., Hammer, G., McLean, G., Messina, C., Roberts, M., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, *3*(5), 497–501. https://doi.org/10.1038/nclimate1832

Lu, J., Carbone, G., & Gao, P. (2017). Detrending crop yield data for spatial visualization of drought impacts in the United States, 1895–2014. *Agricultural and Forest Meteorology*, *237*, 196–208. https://doi.org/10.1016/j.agrformet.2017.02.001

Matiu, M., Ankerst, D., & Menzel, A. (2017). Interactions between temperature and drought in global and regional crop yield variability during 1961–2014. *PLoS One*, *12*(5), 1–23. https://doi.org/10.1371/journal.pone.0178339

Palmer, W. (1965). Meteorological drought. In *U.S. Weather Bureau. Research paper no. 45*.

Portmann, F., Siebert, S., & Döll, P. (2010). MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modelling. *Global Biogeochemical Cycles*, *24*(1), GB1011. https://doi.org/10.1029/2008GB003435

Qi, W., Feng, L., Yang, H., & Liu, J. (2022). Increasing concurrent drought probability in global main crop production countries. *Geophysical Research Letters*, *49*(6), 1–11. https://doi.org/10.1029/2021GL097060

Qing, Y., Wang, S., Ancell, B., & Yang, Z. (2022). Accelerating flash droughts induced by the joint influence of soil moisture depletion and atmospheric aridity. *Nature Communications*, *13*(1), 1139. https://doi.org/10.1038/s41467-022-28752-4

Qing, Y., Wang, S., Yang, Z., & Gentine, P. (2023). Soil moisture−atmosphere feedbacks have triggered the shifts from drought to pluvial conditions since 1980. *Communications Earth & Environment*, *4*(1), 254. https://doi.org/10.1038/s43247-023-00922-2

Raymond, C., Suarez-Gutierrez, L., Kornhuber, K., Pascolini-Campbell, M., Sillmann, J., & Waliser, D. (2022). Increasing spatiotemporal proximity of heat and precipitation extremes in a warming world quantified by a large model ensemble. *Environmental Research Letters*, *17*(3), 035005. https://doi.org/10.1088/1748-9326/AC5712

Ribeiro, F., Russo, A., Gouveia, C., Páscoa, P., & Zscheischler, J. (2020). Risk of crop failure due to compound dry and hot extremes estimated with nested copulas. *Biogeosciences*, *17*(19), 4815–4830. https://doi.org/10.5194/bg-17-4815-2020

Sacks, W., Deryng, D., Foley, J., & Ramankutty, N. (2010). Crop planting dates: An analysis of global patterns. *Global Ecology and Biogeography*, *19*(5), 607–620. https://doi.org/10.1111/J.1466-8238.2010.00551.X

Schauberger, B., Archontoulis, S., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., et al. (2017). Consistent negative response of US crops to high temperatures in observations and crop models. *Nature Communications*, *8*(1), 13931. https://doi.org/10.1038/ncomms13931

Swain, D., Langenbrunner, B., Neelin, J., & Hall, A. (2018). Increasing precipitation volatility in twenty-first-century California. *Nature Climate Change*, *8*(5), 427–433. https://doi.org/10.1038/s41558-018-0140-y

Tan, X., Wu, X., Huang, Z., Fu, J., Tan, X., Deng, S., et al. (2023). Increasing global precipitation whiplash due to anthropogenic greenhouse gas emissions. *Nature Communicatins*, *14*(1), 2796. https://doi.org/10.1038/s41467-023-38510-9

Tigchelaar, M., Battisti, D., Naylor, R., & Ray, D. (2018). Future warming increases probability of globally synchronized maize production shocks. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(26), 6644–6649. https://doi.org/10.1073/pnas.1718031115

Troy, T., Kipgen, C., & Pal, I. (2015). The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters*, *10*(5), 054013. https://doi.org/10.1088/1748-9326/10/5/054013

Venkatappa, M., Sasaki, N., Han, P., & Abe, I. (2021). Impacts of droughts and floods on croplands and crop production in Southeast Asia—An application of Google Earth Engine. *Science of the Total Environment*, *795*, 148829. https://doi.org/10.1016/J.SCITOTENV.2021.148829

Wang, B., Wu, Z., Li, J., Liu, J., Chang, C., Ding, Y., & Wu, G. (2008). How to measure the strength of the East Asian summer monsoon. *Journal of Climate*, *21*(17), 4449–4463. https://doi.org/10.1175/2008JCLI2183.1

Wells, N., Goddard, S., & Hayes, M. (2004). A self-calibrating palmer drought severity index. *Journal of Climate*, *17*(12), 2335–2351. https://doi.org/10.1175/1520-0442(2004)017<2335:ASPDSI>2.0.CO;2

Xiong, Q., Deng, Y., Zhong, L., He, H., & Chen, X. (2018). Effects of drought-flood abrupt alternation on yield and physiological characteristics of rice. *International Journal of Agriculture and Biology*, *20*(5), 1107–1116. https://doi.org/10.17957/IJAB/15.0609

Ye, T., Nie, J., Wang, J., Shi, P., & Wang, Z. (2015). Performance of detrending models of crop yield risk assessment: Evaluation on real and hypothetical yield data. *Stochastic Environmental Research and Risk Assessment*, *29*(1), 109–117. https://doi.org/10.1007/s00477-014-0871-x

You, J., Wang, S., Zhang, B., Raymond, C., & Matthews, T. (2023). Growing threats from swings between hot and wet extremes in a warmer world. *Geophysical Research Letters*, *50*(14), e2023GL104075. https://doi.org/10.1029/2023GL104075

Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A., Fritz, S., et al. (2020). A cultivated planet in 2010—Part 2: The global gridded agricultural-production maps. *Earth System Science Data*, *12*(4), 3545–3572. https://doi.org/10.5194/essd-12-3545-2020

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017). Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, *12*(6), 064008. https://doi.org/10.1088/1748-9326/aa723b

Zhang, B., Wang, S., Moradkhani, H., Slater, L., & Liu, J. (2022). A vine copula-based ensemble projection of precipitation intensity-duration-frequency curves at sub-daily to multi-day time scales. *Water Resources Research*, *58*(11), e2022WR032658. https://doi.org/10.1029/2022WR032658

Zhang, B., Wang, S., Zscheischler, J., & Moradkhani, H. (2023). Higher exposure of poorer people to emerging weather whiplash in a warmer world. *Geophysical Research Letters*, *50*(21), e2023GL105640. https://doi.org/10.1029/2023GL105640

Zhang, H., Xue, Y., Wang, Z., Yang, J., & Zhang, J. (2009). An alternate wetting and moderate soil drying regime improves root and shoot growth in rice. *Crop Science*, *49*(6), 2246–2260. https://doi.org/10.2135/cropsci2009.02.0099

Zhang, Y., You, Q., Ullah, S., Chen, C., Shen, L., & Liu, Z. (2023). Substantial increase in abrupt shifts between drought and flood events in China based on observations and model simulations. *Science of the Total Environment*, *876*, 162822. https://doi.org/10.1016/J.SCITOTENV.2023.162822

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D., Huang, Y., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(35), 9326–9331. https://doi.org/10.1073/pnas.1701762114

Zhao, H., Zhang, L., Kirkham, M., Welch, S., Nielsen-Gammon, J., Bai, G., et al. (2022). U.S. winter wheat yield loss attributed to compound hot-dry-windy events. *Nature Communications*, *13*(1), 1–9. https://doi.org/10.1038/s41467-022-34947-6

Zhu, P., Abramoff, R., Makowski, D., & Ciais, P. (2021). Uncovering the past and future climate drivers of wheat yield shocks in Europe with machine learning. *Earth's Future*, *9*(5), 1–13. https://doi.org/10.1029/2020EF001815

Zhu, R., Wu, F., Zhou, S., Hu, T., Huang, J., & Gao, Y. (2020). Cumulative effects of drought–flood abrupt alternation on the photosynthetic characteristics of rice. *Environmental and Experimental Botany*, *169*(July 2019), 103901. https://doi.org/10.1016/j.envexpbot.2019.103901

Zhu, X., & Troy, T. (2018). Agriculturally relevant climate extremes and their trends in the world's major growing regions. *Earth's Future*, *6*(4), 656–672. https://doi.org/10.1002/2017EF000687

Zscheischler, J., & Fischer, E. (2020). The record-breaking compound hot and dry 2018 growing season in Germany. *Weather and Climate Extremes*, *29*, 100270. https://doi.org/10.1016/j.wace.2020.100270

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R., et al. (2020). A typology of compound weather and climate events. *Nature Reviews Earth & Environment*, *1*(7), 333–347. https://doi.org/10.1038/s43017-020-0060-z

Zscheischler, J., Westra, S., Hurk, B., Seneviratne, S., Ward, P., Pitman, A., et al. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3

References From the Supporting Information

Adams, B., Mann, M., & Ammann, C. (2003). Proxy evidence for an El Niño-like response to volcanic forcing. *Nature*, *426*(6964), 274–278. https://doi.org/10.1038/nature02101

Amin, M., Aryan, S., Habibi, N., Kakar, K., & Zahid, T. (2022). Elucidation of photosynthesis and yield performance of rice (*Oryza sativa L.*) under drought stress conditions. *Plant Physiology Reports*, *27*(1), 143–151. https://doi.org/10.1007/s40502-021-00613-0

Davi, N., D'Arrigo, R., Jacoby, G., Cook, E., Anchukaitis, K., Nachin, B., et al. (2015). A long-term context (931–2005 CE) for rapid warming over Central Asia. *Quaternary Science Reviews*, *121*, 89–97. https://doi.org/10.1016/j.quascirev.2015.05.020

Fahad, S., Bajwa, A., Nazir, U., Anjum, S., Farooq, A., Zohaib, A., et al. (2017). Crop production under drought and heat stress: Plant responses and management options. *Frontiers in Plant Science*, *8*, 1147. https://doi.org/10.3389/fpls.2017.01147

Haurwitz, M., & Brier, G. (1981). A critique of the superposed epoch analysis method: Its application to solar–weather relations. *Monthly Weather Review*, *109*(10), 2074–2079. https://doi.org/10.1175/1520-0493(1981)109<2074:ACOTSE>2.0.CO;2

He, Y., Hu, X., Xu, W., Fang, J., & Shi, P. (2022). Increased probability and severity of compound dry and hot growing seasons over world's major croplands. *Science of the Total Environment*, *824*, 153885. https://doi.org/10.1016/J.SCITOTENV.2022.153885

Laborte, A., Gutierrez, M., Balanza, J., Saito, K., Zwart, S., Boschetti, M., et al. (2017). RiceAtlas, a spatial database of global rice calendars and production. *Scientific Data*, *4*, 1–10. https://doi.org/10.1038/sdata.2017.74

Liu, L., Hong, Y., Bednarczyk, C., Yong, B., Shafer, M., Riley, R., & Hocker, J. (2012). Hydro-climatological drought analyses and projections using meteorological and hydrological drought indices: A case study in Blue river basin, Oklahoma. *Water Resources Management*, *26*(10), 2761–2779. https://doi.org/10.1007/s11269-012-0044-y

Lee, M., Kang, B., Lee, J., Choi, W., Ko, J., Choi, J., et al. (2013). How do extreme wet events affect rice quality in a changing climate? *Agriculture, Ecosystems & Environment*, *171*, 47–54. https://doi.org/10.1016/J.AGEE.2013.03.006

Rao, M., Cook, E., Cook, B., Anchukaitis, K., D'Arrigo, R., Krusic, P., & LeGrande, A. (2019). A double bootstrap approach to superposed epoch analysis to evaluate response uncertainty. *Dendrochronologia*, *55*, 119–124. https://doi.org/10.1016/j.dendro.2019.05.001

Thornthwaite, C. (1948). An approach toward a rational classification of climate. *Geographical Review*, *38*(1), 55. https://doi.org/10.2307/210739

Win, A., Tanaka, T., & Matsui, T. (2020). Panicle inclination influences pollination stability of rice (*Oryza sativa L.*). *Plant Production Science*, *23*(1), 60–68. https://doi.org/10.1080/1343943X.2019.1698971